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# Hybrid Optimization algorithm for parameter estimation of poly-phase induction motors with experimental verification

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**Abstract-** The estimated parameters accuracy of poly-phase induction motors is crucial for effective performance prediction and/or control in various manufacturing applications. This study investigates hybrid algorithm between particle swarm optimization and Jaya optimization algorithms for finding the optimal parameters estimation of poly-phase induction motors. It is carried out using the manufacturer's operation characteristics on two poly-phase induction motors. Numerical results show the capability of the proposed hybrid optimization algorithm. The proposed algorithm has competitive performance compared with conventional algorithms as well as with differential evolution and genetic algorithms. Experimental verifications are carried out on three-phase and six-phase induction motors. Also, it emulates the closeness between experimental and estimated parameters with fast convergence compared to other algorithms. Also, the results reflect the high robustness of the proposed algorithm compared with other algorithms for varied iteration numbers, population size and convergence.

**Keywords:** HPJOA, Poly-phase induction motors, Parameter estimation, Statistical analysis, Robustness, Experimental tests.

## Nomenclature

$R_s$	Per phase stator resistance, $\Omega$ .	$eT_d$	Estimated developed torques
$R_2$	Per phase rotor resistance, $\Omega$ .	$mT_{max}$	Measured maximum developed torques
$X_s$	Per phase stator reactance, $\Omega$ .	$eT_{max}$	Estimated maximum developed torques
$X_2$	Per phase rotor reactance, $\Omega$ .	$mT_{st}$	Measured starting developed

			torques
$X_m$	Per phase magnetizing reactance, $\Omega$ .	$eT_{st}$	Estimated starting developed torques
$V_{ph}$	Per phase stator voltage, V.	$s_{mT}$	Slip at maximum torque
$p$	number of pole pairs	$\Delta F$	objective function
$T_d$	electromagnetic torque of the motor, N.m	$\Delta pf$	Normalized power factor
$s$	Induction motor slip	$\Delta T_{st}$	Normalized power factor
$I_2$	Per phase rotor current, A.	$\Delta T_{max}$	Normalized power factor
$I_s$	Per phase stator current, A.	$pf$	Rated power factor
$I_{st}$	starting current, A.	$m$	Number of phases
$T_{st}$	starting torque of the motor, N.m	$epf$	Estimated power factors
$T_{max}$	maximum torque of the motor, N.m	$mpf$	Measured power factors
$T_{FL}$	rated torque of the motor, N.m	$mT_d$	Measured developed torques
$\Delta T_d$	Normalized power factor	$k$	Iteration number
$v$	velocity of the control variables	$c_1, c_2, c_3$	The learning coefficients
$F_k^{best}$	personal best of control variables	$r_1, r_2, r_3$	random numbers
$gF_k^{best}$	global best of control variables	$Iter^{max}$	maximum number of iterations.
$\Delta F_k^{worst}$	worst suggested of possible solution		

## 1. Introduction

The Poly-phase Induction Motors (PIMs) are the most used electrical machines[1]. They contribute around 60% of electric power converted to mechanical energy [2]. PIM are favored due to their ruggedness and simplicity in the industry section as 90% of industrial motors are IMs [3]. Examples of induction motors applications involve motor tools equipped with induction motors, adjustable speed motors and pumps[4]. To achieve the target performance of induction machines, the accurate modelling is considered as crucial issue for PIMs [5]. These issues involve the transient and steady-state behavior. The model expresses the stator and rotor windings voltage balance, flux linkages and currents, the air-gap power, and the electromagnetic torques. Therefore, finding the unknown parameters of these machines is a complicated nonlinear non-smooth optimization problem [6]. It aims at achieving the highest closeness degree between the estimated parameters and those of the actual ones. Therefore, the objective function of the considered parameter estimation problem is the minimum deviation between estimated and actual parameters with preserving these parameters within

their permissible operating boundaries. To satisfy the parameter identification process, several optimization algorithms have been developed to guarantee the accurate PIM models. In this regard, this paper proposes the **hybrid algorithm between particle swarm optimization and Jaya optimization algorithms** HPJOA form finding the optimal unknown PIM parameters.

The modelling of induction motors is considered as vital issue in ac drive systems. Accurate parameters identification of induction motor is an urgent work in the viewpoint of control drives and operation aspects [7], [8]. **It is necessary to find the IMs' parameters at low implementation costs at high degree of accuracy.** The traditional methods applied for finding the equivalent circuit parameters are dependent on no-load and locked rotor tests as in IEEE Std 112-1991 and its modifications IEEE Std 112-2004 [9]. Added to that, the high cost of hardware that is needed to implement. So, Due to these restrictions, many optimization methods developers provide number of advanced methods to meet the target of finding satisfactory level of the estimated parameters [10]. **For achieving this target, several optimization methods are exploited to optimally estimating the parameter of PIMs equivalent circuits**[11]–[13]. In the literature, several methods have been carried out for finding the unknown parameters of PIMs. References[14] and[10] review the various methods that were developed for estimating the unknown parameters of PIMs. In this line, the previous efforts are summarised as follows:

- Reference [15] developed the artificial immune system for extracting the IM parameters to optimize the parameters of IMs from experimental tests and manufacturer data.
- Reference[16] presented the neural network as training mechanism for finding the solution of parameter estimation problem.
- **Reference[17], [18] presented the shuffled frog-leaping for extract the equivalent circuit parameters of IMs from the manufacturer data.**
- **Reference[19] presented a simplified model for parameter estimation of the PIMs.**
- Reference[20] estimated the 6-phase IM parameters using modified standard tests. This zero-sequence test is proceed using an improved equivalent circuit to enhance the estimated parameter accuracy.
- Reference [21] developed multi-objective **PSO** algorithm to minimize the deviation between the manufacturer and estimated data.
- Reference[22] developed differential evolution for finding the parameter estimation of three phase IMs.

The previous **survey** shows the application of various optimization techniques for solving the parameter estimation problem. The field of optimization is continuous and worth of interest. **Many optimization algorithms were developed for many real engineering problems as: moth-flame [23], fruit fly [24], cat swarm [25], sunflower [26], wind driven [27], and water cycle [28] optimization algorithms.** Among the optimization algorithm, PSO algorithm that mimics the main idea of fish or birds looking for

food was introduced in by Eberhart and Kennedy [29] . Several real-world works are reported based on PSO algorithm and its variants in the literature. Reference[30] presented an intelligent diagnosis method using, design of synchronous motor [31], optimization of PID controller parameters adjustment [32], optimal costs of generation production [33]. The main drawback of PSO is the need to adjust learning and inertia coefficients.

An efficient metaheuristic technique called PSO it was started by Kennedy and Eberhart was presented in Ref.[34]. This algorithm was taken from swarm attitude such as bird flow and education in nature[31]. Particles that move inside the problem are used at high speeds [35]. In every repetition, the velocities of the self-particles are randomly preset related to the best position of the same particle and the best position of the near particle. The best particles and the best close ones are selected according to the conditions set by the user. The transition of all particles occurs normally to the best solution. The word "swarm" originates from the unequal movement of particles in the problem area, and now very much resembles a group of fish or birds [36]. The Jaya algorithm [37] is one of the recent metaheuristic techniques which is quickly finding many applications in different fields of engineering and science. The JOA directed the solution towards the best value with the progress of the optimization algorithm[38]. The main merits of JOA are its simplicity and the benefits of no need for adopting and selecting the specific control parameters that avoid the demerits of PSO algorithm. JOA is very promising optimizer which is developed for many real-world applications as: optimal sizing of capacitor-bank types in the low voltage distribution networks[39], control of online load frequency in wind power systems [40], solving economic/emission unit commitment[41]. Added to the previous applications, JOAs is applied for harmonic mitigation and employing reactive power compensation of three phase induction motor that drives by photo-voltaic-based DSTATCOM [42], automatic generation control of multi-area interconnected power system [43], for optimal power flow [44], environment based allocation of distributed energy resources in a micro-grid [45] for optimizing the thermal performance of the underground power cable system[46], for reactive power dispatch problem [47], and for design the digital FIR filters in [48].

As mentioned, the problem is formulated as non-linear optimization problem because the conventional optimization techniques fail to deal exactly with the need of linearization that reduces the solution quality and high dependency on the initial point of linearization. So, it must seek other methods to solve the non-linear optimization problem avoiding the previous drawbacks. The features of this paper are concluded as follows:

- The steady state model of multi-phase induction motor is derived.
- The Hybrid PSO-Jaya optimization algorithm is proposed to extract the optimal unknown parameters of PIM from the nameplate data.

- The performance of HPJOA is assessed compared with Jaya, GA, DE and PSO optimization algorithms for three and six-phase induction motors.
- The assessment study proves that the HPJOA has the fast response compared with other competitive algorithms with **actual** parameters.
- Also, the results reflect the high robustness of the proposed HPJOA compared with others.

The rest sections are organized as follows: In section 2, the steady state characteristics of poly-phase IM is presented based on equivalent circuit. In Section 3, the parameter estimation problem is formulated as an optimization problem that defines the objective and constraints. The previous optimization algorithms are **added to section 4. The design procedure of HPJOA is presented in Section 5. In Section 6, the parameter estimation problem and its operation characteristic are applied on two poly-phase IMs. Section 7** concludes the paper findings.

## 2. Steady state characteristics of poly-phase induction motor

The steady state operating characteristics are identified based on the steady state equivalent circuit shown in Figure 1. The equivalent circuit shows the per phase steady state equivalent circuit of poly-phase induction motor without separate mutual leakage inductance of stator winding [20]. The stator and magnetizing impedance in poly-phase induction motor can be reduced to the Thevenin equivalent circuit as shown in Figure 2. The Thevenin voltage is computed through:

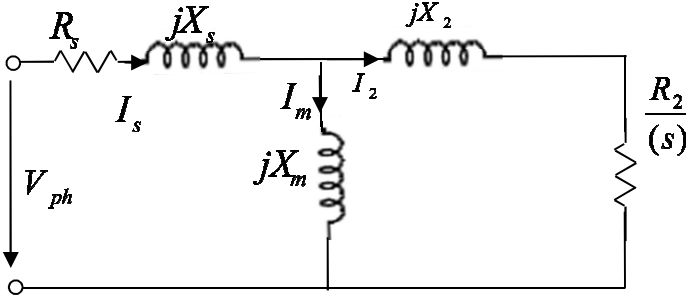


Fig. 1: multi-phase induction motor equivalent circuit

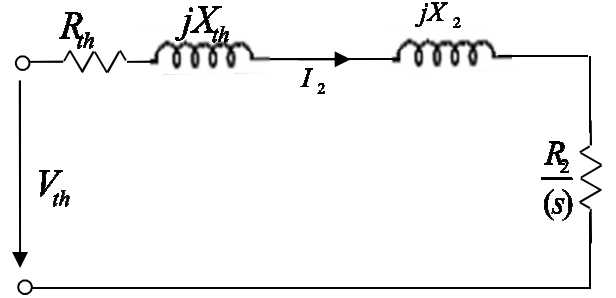


Fig. 2: Thevenin equivalent circuit

$$V_{th} = \frac{jX_m}{R_s + jX_s + jX_m} V_{ph} \quad (1)$$

The Thevenin equivalent circuit of poly phase induction motor(PIM)is shown in Fig.2 as:

$$Z_{th} = R_{th} + jX_{th} = \frac{jX_m(R_s + jX_s)}{R_s + jX_s + jX_m} = \frac{R_s X_m}{X_s + X_m} + j \frac{X_m X_s}{X_s + X_m} \quad (2)$$

The current flow in the IM rotor circuit of induction motor can be calculated as:

$$I_2 = \frac{V_{th}}{Z_{th} + Z_2} = \frac{V_{th}}{\left(R_{th} + \frac{R_2}{s}\right) + j(X_{th} + X_2)} \quad (3)$$

The developed torque can be determined by Eq. (4) as:

$$T_d = \frac{m}{\omega_s} I_2^2 \frac{R_2}{s} = \frac{m}{\omega_s} \frac{V_{th}^2}{\left(R_{th} + \frac{R_2}{s}\right)^2 + (X_{th} + X_2)^2} \frac{R_2}{s} \quad (4)$$

From the above equation the slip at maximum torque  $s_{mT}$  can be calculate from

$$s_{mT} = \frac{R_2}{\sqrt{(R_{th})^2 + (X_{th} + X_2)^2}} \quad (5)$$

Substituting the slip at maximum torque from Eq.(5) into the electromagnetic torque in Eq.(4) the maximum torque can be calculated from:

$$T_{max} = \frac{m}{2\omega_s} \frac{V_{th}^2}{\left[R_{th} + \sqrt{(R_{th})^2 + (X_{th} + X_2)^2}\right]} \quad (6)$$

The Starting torque can be calculated from

$$T_{st} = \frac{m}{\omega_s} \frac{V_{th}^2}{(R_{th} + R_2)^2 + (X_{th} + X_2)^2} R_2 \quad (7)$$

The input current power factor can be obtained from

$$pf = \cos \left( \tan^{-1} \left( \frac{X_{th} + X_2}{R_{th} + \frac{R_2}{s}} \right) \right) \quad (8)$$

### 3. Problem formulation

The fitness function aims at finding the lowest deviation level for the starting, operating , maximum torques and the power factor. This fitness function assures the capability of estimated parameters at different operating conditions. Equation (9) presents the combined fitness function for finding the optimal parameter estimation of the tested induction motors. It aims at minimizing the deviation between the estimated and experimental data. The combined objective function, in Eq. 9, has four normalized deviation components for the starting, rated and maximum torques, and the full load power factor as:

$$\Delta F = \Delta T_d^2 + \Delta T_{max}^2 + \Delta T_{st}^2 + \Delta pf^2 \quad (9)$$

Computing the normalized components is carried out using Eqs. (10)-(13) as:

$$\Delta pf = \frac{epf - mpf}{mpf} \quad (10)$$

$$\Delta T_d = \frac{eT_d - mT_d}{mT_d} \quad (11)$$

$$\Delta T_{\max} = \frac{eT_{\max} - mT_{\max}}{mT_{\max}} \quad (12)$$

$$\Delta T_{st} = \frac{eT_{st} - mT_{st}}{mT_{st}} \quad (13)$$

where  $\Delta F$  is assumed as the required objective square error function of full load, starting, and maximum torque, and rated power factor which is to be minimized.

Equation 9 is solved subject to the minimum and maximum limitations of the stator and rotor sides' motor parameters.

#### 4. The developed optimization algorithms

In the following section, the GA, DE, PSO, and JAYA are described in details as:

##### A) Differential evolution DE

Differential evolution DE is algorithm based on stochastic and population. The population is composed of pop individuals and every individual in the population represents a solution that possible to minimize the fitness function. DE operates in three sequential steps in all iteration[22]:

1. Mutation: pop mutated individuals are generated using some individuals of the population. A vector for the mutated solution is called mutant vector. There are different strategies to create a mutant vector. Here only the three most common mutation methods are explained [49]. Other mutation strategies and their performance have been discussed in.
  - i. Mutation strategy is random mutation strategy, in which three randomly selected individuals from the population are used to generate the mutant vector.
  - ii. Mutation strategy uses the best individual from the population to create the mutant vectors.
  - iii. The mutation strategy moves the current individual towards the best individual in the population before being disturbed with a scaled difference of two randomly selected individuals.
2. Crossover: we recombine the set of mutant vectors created in mutation with the original population members to generate progeny solutions.



Selection: In this last step, the progeny is compared with its origin, and the best one will but the population for the next generation

### **B) Genetic algorithm GA**

GA is an evolutionary optimizer that takes a sample of possible solutions and employs mutation, crossover, and selection as the primary operators for optimization. For the case of multi-phase induction motor parameters estimation, there are five parameters being optimized for the multi-phase induction motor parameters estimation [35].

The workability of GAs is based on Darwinian's theory of survival of the fittest. Genetic algorithms may contain a chromosome, a gene, and set of population, fitness, fitness function, breeding, mutation and selection. Genetic algorithms begin with a set of solutions represented by chromosomes, called population [50]. Solutions from one population are taken and used to form a new population, which is motivated by the possibility that the new population will be better than the old one. Further, solutions are selected according to their fitness to form new solutions, that is, offspring's.

The solution procedure of the parameters estimation problem can be carried out using the proposed GA optimization algorithm as follows:

1. Start: Generate random population of chromosomes, that is, suitable solutions for the problem.
2. Fitness: Evaluate the fitness of each chromosome in the population.
3. New population: Create a new population by repeating following steps until the new population is complete.
  - i. Selection: Select two parent chromosomes from a population according to their fitness. Better the fitness, the bigger chance to be selected to be the parent.
  - ii. Crossover: With a crossover probability, cross over the parents to form new offspring, that is, children. If no crossover was performed, offspring is the exact copy of parents.
  - iii. Mutation: With a mutation probability, mutate new offspring at each locus.
  - iv. Apply: Place new offspring in the new population.
4. Update: Use new generated population for a further run of the algorithm.
5. Check: If the end condition is satisfied, stop, and return the best solution in current population.

### **C) PSO algorithm**

The Particle Swarm Optimization is configured with a set of random results and seeks to improve by updating generations. In PSO, the possible solutions, called particles, flythrough the problem space by following the current optimum particles [31]. In PSO, a set of randomly initial swarm propagates in the design space towards the optimal solution over a number of iterations based on large amount of information about the design space that is assimilated and shared by all members of the swarm.

Modification of the swarm agent positions is realized by the position and transition information. Each agent transition can be simulated by two dimensional referred to the available information's about self and group experiences. The basic PSO version is based on the collected information of self and group experiences according to the positions of agents.

The basic PSO is presented as in [34] as:

$$\begin{aligned}\Delta x_{k+1} &= v_k \cdot \Delta x_k + c_1 \times r_1 \times (x_k^{best} - x_k) + c_2 \times r_2 \times (xg_k^{best} - x_k) \\ x_{k+1} &= x_k + \Delta x_{k+1}\end{aligned}\quad (14)$$

where,  $x_k$ ,  $x_k^{best}$  is the vector of control variables and personal best of control variables at iteration  $k$ .  $xg_k^{best}$  is the vector of global best of control variables at iteration  $k$ ,  $x_{k+1}$  is the vector of control variables at iteration  $k+1$ .

The velocity of the control variables updated at iteration  $k$  is:

$$v_k = v_k^{\max} - (v_k^{\max} - v_k^{\min}) \times k / Iter^{\max} \quad (15)$$

Where  $v_k^{\max}$  and  $v_k^{\min}$  is a function of search space length in each dimension,  $Iter^{\max}$  is the maximum number of iterations. The learning coefficients  $c_1$  and  $c_2$  are the factors which PSO technique optimizes different objective functions on the basis of personal and group experiences and each agent tries to modify its position the updating formula (14).

The minimum and maximum transition of the updating formula in (14) for agent position as:

$$\Delta x^{\min} \leq \Delta x_k \leq \Delta x^{\max} \quad (16)$$

where:

$$\begin{cases} \Delta x^{\max} = k_m (x_k^{\max} - x_k^{\min}) \\ \Delta x^{\min} = -k_m (x_k^{\max} - x_k^{\min}) \end{cases} \quad (17)$$

#### D) JAYA optimization algorithm

The Jaya optimization algorithm (JOA) replaces the updating formula in PSO algorithm by the following equation as[51], [52]. The main advantage of JOA is characterized with the high ability of movement in the direction of the best solution and avoiding the possibility of trapping into worst solutions. The combination of these two terms concentrates on the best solution region [53]. Two global solutions, reflected in the updating equation terms, the best and worst solution for the overall particles. But, JOA is not dependent on the self-experience of particle as in PSO algorithm[54]. Then, the updating equation has two terms the first enhances the closeness between the best solutions while the second terms avoid the closeness to worst solution.

The updating equation is expressed as:

$$x_{k+1} = x_k + r_1 \times (x_k^{best} - \Delta x_k) - r_2 \times (x_k^{worst} - x_k) \quad (18)$$

where,  $x_k^{best}$ ,  $x_k^{worst}$  are the value of the variable  $k$  for the best and worst suggested member of a set of possible solution.  $r_1$  and  $r_2$  are two random numbers in the range (0,1).

## 5. The proposed hybrid PSO -JAYA optimization algorithm

The proposed hybrid optimization algorithm combines the merits of PSO and Jaya algorithms. It enhances the search space, forces the solution to the global best solution and away from the worst solutions. Equation (19) presents the updating formula for the proposed HPJOA. It is dependent on the global best, worst solution and taken into consideration the impact of self-experience of the associated particles.

The proposed updating equation can be expressed as:

$$x_{k+1} = v_k x_k + c_1 \times r_1 \times (x_k^{best} - x_k) - c_2 \times r_2 \times (x_k^{worst} - x_k) + c_3 \times r_3 \times (x_k^{gbest} - x_k) \quad (19)$$

where,  $x_k^{gbest}$  is the value of the variable  $k$  for the global member of a set of possible solution. For the  $k^{th}$  iteration in the range of (0, 1),  $r_1$ ,  $r_2$  and  $r_3$  are the three random numbers for the  $k^{th}$  variable.  $c_1$ ,  $c_2$  and  $c_3$  are learning coefficients, the first term shows the affinity of solution to move nearer to the personal best solution, The second term shows the affinity of solution to move nearer to the global best solution and the last term is the tendency of the solution to avoid the worst solution.

### 5.1 Proposed procedure steps

The proposed procedure of HPJOA can be carried out as follows:

1. Defining the motor manufacture data, parameters limits, constraints and the HPJOA coefficients.
2. Initialize the control variables (estimation variables) within the predefined boundaries.
3. Evaluate each particle of the initialized matrix by determining the fitness function through solving the steady state equivalent circuit.
4. Identify the global, personal and worst solutions.
5. Update the control variables using equation (19).
6. Check the upper and lower boundaries and transition constraints given in equations (16) and (17).
7. The reduction strategy to concentrate the search space and there for enhance the solution quality.

The factor  $\alpha$  refers to the coefficient applied for reduction strategy. In this strategy, the search space is managed through adaptive variation of the upper and lower limits according to the following two equations:

$$\min v = \min v + \alpha \times (\max v - \min v) \quad (20)$$

$$\max v = \max v - \alpha \times (\max v - \min v) \quad (21)$$

In this paper the factor  $\alpha$  equals 0.08.

8. Repeat steps 3 to 4 until the maximum iteration as stopping criteria are achieved. Figure 3 shows the flow chart of HPJOA.

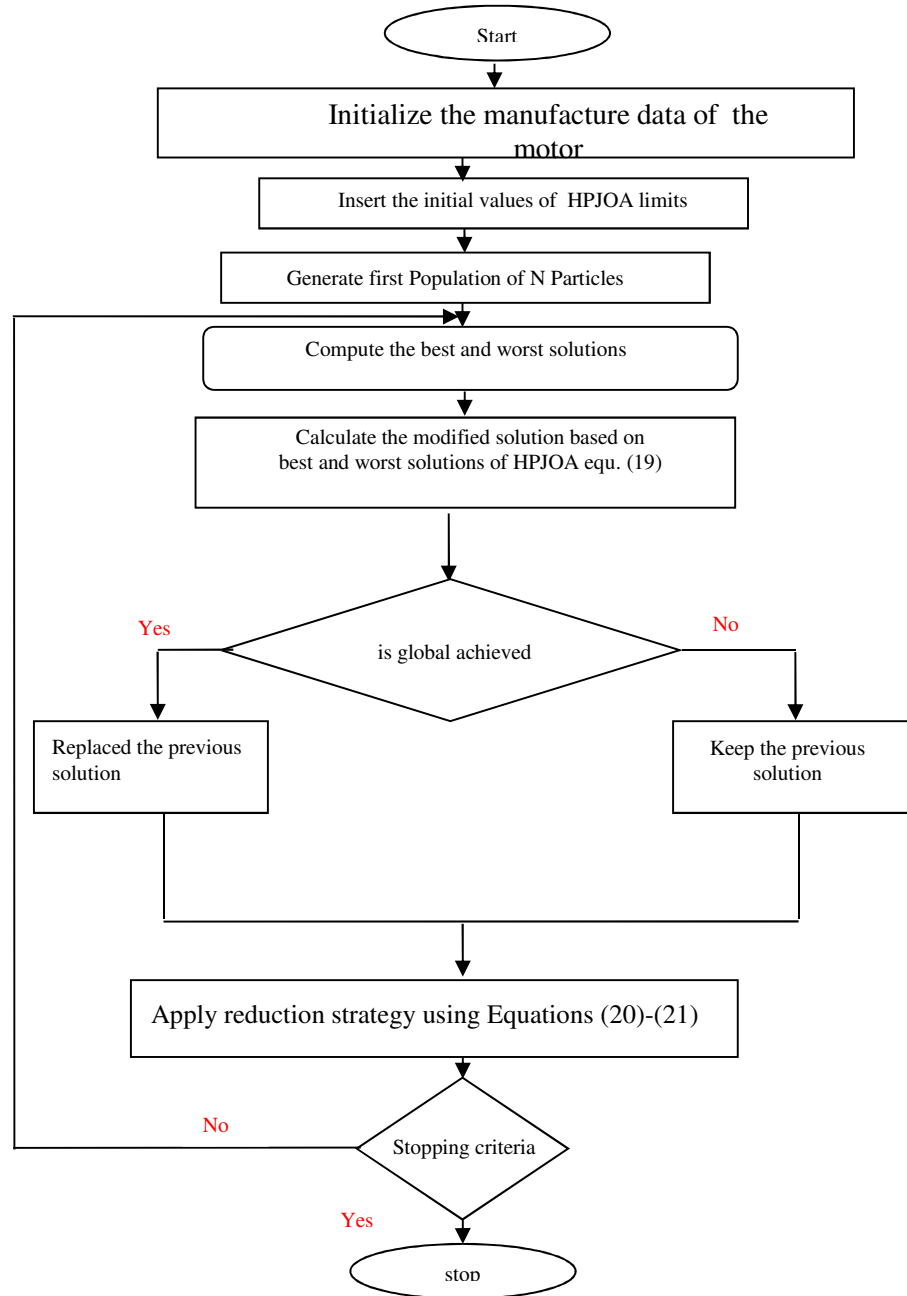


Fig. 3: Flowchart for Hybrid PSO-Jaya Based Optimization Process

## 6 Applications

### 6.1. Experimental Setup

The experimental tests- open, short circuit and DC tests- are carried out on two poly-phase IM to obtain the equivalent circuit parameters. Photograph of the experimental implementation located at Faculty of Engineering; Kafrelsheikh University is provided in Figure 4. The tests are carried out according to the specifications of the IEEE Std 112<sup>TM</sup>-2004 for tests procedure for PIM [6]. Table 1 represents the recorded measurements for three-phase and six-phase IMs. By using the data recorded for voltage, current, input power and the dc resistances from no load, short circuit and short circuit tests in Table 1. These records are used to determine the three and six phase induction motor parameters by using the proposed hybrid HPJOA and the competitive algorithms..

Table 1: Experimental tests of 1/3 HP three-phase and 3 HP six-phase IMs.

Variables	Three phase IM (1/3 HP)		Six phase IM (3 HP)	
	No load test	Short-circuit test	No load test	Short-circuit test
Voltage, V	220	89.7	220	96.9
Current, A	0.22	0.65	0.95	2.67
Input power, W	9.5	25.6	104	159.37
$R_{dc}$ $\Omega$	21.25		12	



Figure 4: Experimental setup at Faculty of Engineering, Kafrelsheikh University.

## 6.2. Settings of competitive optimization algorithms' parameters

The parameters setting for the competitive algorithms are described as follows:

1. Maximum iteration number is 100 and the population size is 60.
2. For GA [35], the parameters were set crossover length = 0.5, resolution = 3, and mutation probability = 0.12. For DE[22] [49], the parameters were set crossover probability = 0.7 and scaling factor = 0.5, mutation probability = 0.5. Finally, for HPJOA, the parameters are  $c_1 = 1$ ,  $c_2 = 2$ ,  $c_3 = 1.5$  and search space length were set  $v_k^{\max} = 0.8$ , and  $v_k^{\min} = 0.3$ .

### Case 1: three phase induction motor parameter estimation

The competitive algorithms are integrated to obtain the parameter estimations of 1/3 HP three-phase induction motor. The experimental parameters of the steady state equivalent circuit of the 3 phase induction motor are shown in the second column of Table 2. The estimated parameters of steady-state equivalent circuit of three phase induction motor using PSO, JOA, GA, DE and HPJOA methods are reported in the rest of columns of the Table 2. The obtained results show that the parameters by using the proposed HPJOA are closer to actual value of motor than PSO and JOA, GA and DE. In the viewpoint of operational indices, a comparison is carried out between the estimated and the experimental values of the starting, maximum, full load torques, and full load power factor. The HPJOA has the lower fitness function ( $1.71 \times 10^{-6}$ ) compared with Jaya method which equals ( $2.9 \times 10^{-5}$ ), with PSO method which equals ( $9.25 \times 10^{-5}$ ), with GA method which equals ( $4.84 \times 10^{-5}$ ) and with DE method which equals ( $1.98 \times 10^{-4}$ ). It is cleared that, the proposed HPJOA achieves the hoiesht reduction of 91.36% improvement is occurred with the largest fitness function obtained with DE.

Table 2: Assessment of competitive algorithms for 3-phase induction motor

Parameters	Experimental	DE	PSO	GA	Jaya	HPJOA
$R_s$	21.25	19.46	21.53	20.21	21.33	21.177
$X_s$	61.95	63.42	60.40	60.62	61.87	61.01
$R_r$	39.32	40.08	39.379	39.93	39.42	39.352
$X_r$	61.95	62.74	63.78	64.99	62.03	63.07
$X_m$	999.52	1049.5	1012.1	1045	1005.3	1000.1
$T_{st}$	0.89	0.889	0.89	0.889	0.89	0.89
$T_{FL}$	0.987	0.981	0.988	0.985	0.992	0.988
$T_{max}$	1.435	1.44	1.433	1.43	1.439	1.436
$Pf$	0.807	0.810	0.808	0.811	0.807	0.806
$\Delta F \times 10^{-4}$		1.98	0.924	0.484	0.29	0.0171

<i>% reduction</i>	-	53.33%	25.56%	85.35%	91.36%
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### Case 2: Six phase induction motor parameter estimation

Table 3 shows the experimental tests are recorded for the 3 HP modified six-phase induction motor. To confirm the proposed HP JOA algorithm is performed for parameter estimation. While the estimated parameters of steady-state equivalent circuit of six phase induction motor using PSO, Jaya and Hybrid PSO-Jaya methods are recorded in Table 4, receptively. The comparison between the experimental and estimated parameters concludes that the investigated estimation algorithms can accurately estimate the equivalent circuit parameter at acceptable levels of closeness. The estimated parameters obtained by using HPJOA are closer to actual value of motor and it has smaller error than Jaya, and PSO. The Hybrid PSO-Jaya optimization algorithm has lower fitness function ( $2.08 \times 10^{-6}$ ) compared with Jaya method which equals ( $7.88 \times 10^{-5}$ ), with PSO method which equals ( $9.63 \times 10^{-5}$ ), with GA method which equals ( $3.29 \times 10^{-5}$ ) and with DE method which equals ( $7.91 \times 10^{-5}$ ). It is cleared that, the proposed HPJOA achieves the highest reduction of 97.84% improvement is occurred with the largest fitness function obtained with PSO.

Table 3: Assessment of competitive algorithms for six-phase induction motor

<i>Parameters</i>	<i>Experimental</i>	<i>PSO</i>	<i>DE</i>	<i>Jaya</i>	<i>GA</i>	<i>HPJOA</i>
$R_s$	12	11.63	11.38	11.65	12.4	11.898
$X_s$	12.8426	13.86	12.74	13.78	12.65	13.095
$R_r$	8.0978	8.12	8.26	8.105	8.04	8.092
$X_r$	12.8426	12.14	13.69	12.13	12.65	12.66
$X_m$	266.68	273.55	268.41	274.29	268.27	263.66
$T_{st}$	3.34	3.348	3.35	3.36	3.348	3.34
$T_{FL}$	3.1785	3.17	3.16	3.18	3.183	3.18
$T_{max}$	5.36	5.377	5.38	5.386	5.339	5.36
$Pf$	0.844	0.846	0.84	0.847	0.847	0.842
$\Delta F \times 10^{-4}$		0.963	0.791	0.788	0.329	0.0208
% reduction		-	17.86%	18.18%	65.84%	97.84%

### 6.3 Performance of operating characteristic with estimated parameters

Figure 5 shows the three-phase induction motor torque-slip characteristic using parameters that was recorded from the measurements clearly, that the parameters estimated from optimization PSO, that the

parameters estimated from optimization Jaya, that the parameters estimated from optimization GA, **that** the parameters estimated from optimization DE, and that the parameters estimated from the proposed HPJOA. Estimated **torque-slip** characteristic, using parameters calculated by DE, has a little difference compared to the measured **torque-slip** characteristic, while estimated curve using parameters obtained by the HPJOA is very close to real characteristic.

The stator-**slip** and rotor current-**slip** characteristics using parameters estimated by the five algorithms are shown in Figures 6a, b. Estimated stator and rotor current characteristics using parameters calculated by **PSO** has **large** difference compared to the measured characteristics, while estimated characteristics using parameters calculated by the HPJOA is very close to the real characteristics. The magnetizing current-**slip** and power factor-**slip** characteristics of three-phase induction motor using parameters calculated by the PSO, Jaya, GA, DE and HPJOA are shown in Figure 6 c, d. Estimated magnetizing current and power factor characteristics using parameters calculated by PSO, Jaya, GA and DE have big difference compared to the measured characteristics, while estimated characteristics using parameters calculated by the HPJOA is very close to the real characteristics.

Figure 7 shows the six-phase induction motor parameters estimated from the measurements clearly, that the parameters estimated from optimization PSO, that the parameters estimated from optimization Jaya, GA, DE and that the parameters estimated from the proposed hybrid algorithm. Estimated torque-speed characteristic using parameters calculated by PSO, Jaya, GA and DE have little differences compared to the measured torque speed characteristic, while estimated curve using parameters obtained by the proposed algorithm is very close to real characteristic.



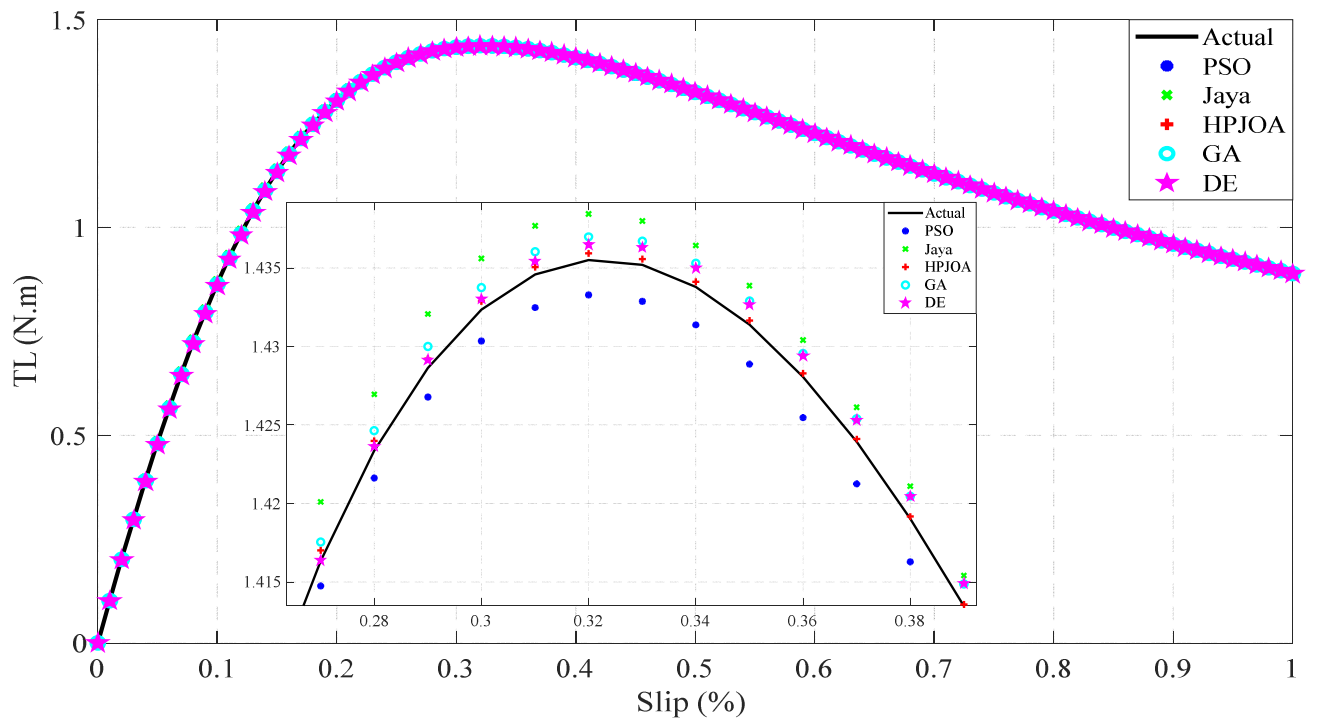
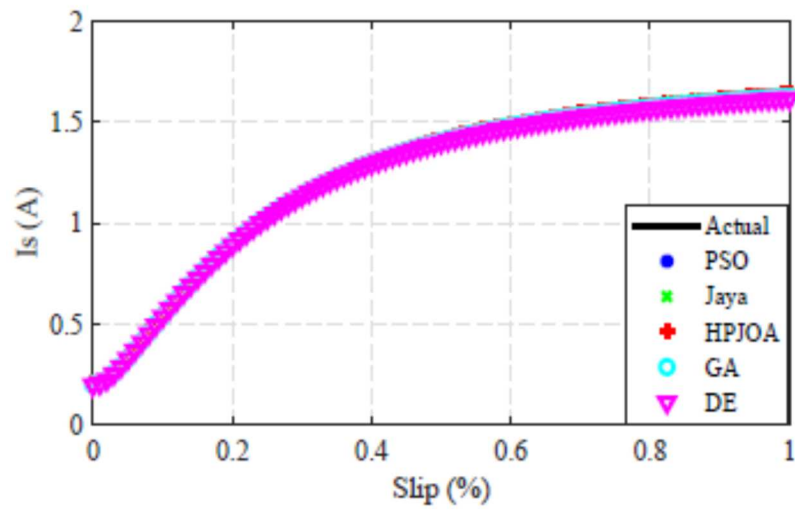
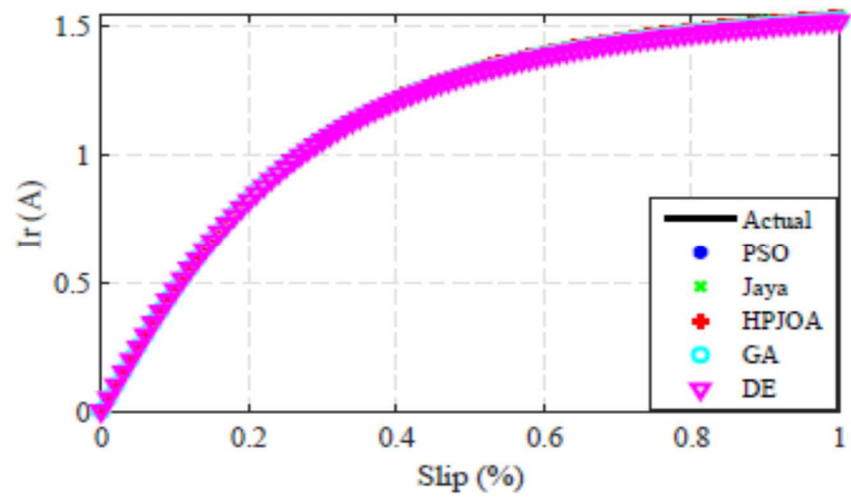


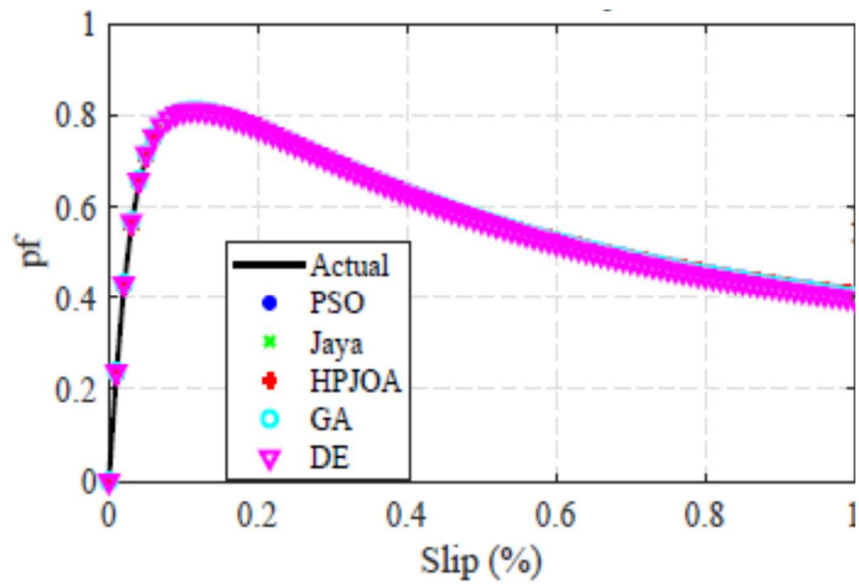
Fig. 5: Electromagnetic torque - slip characteristics of three phase IM (-measurement, \* PSO, × Jaya, o GA, DE, +HPJOA).



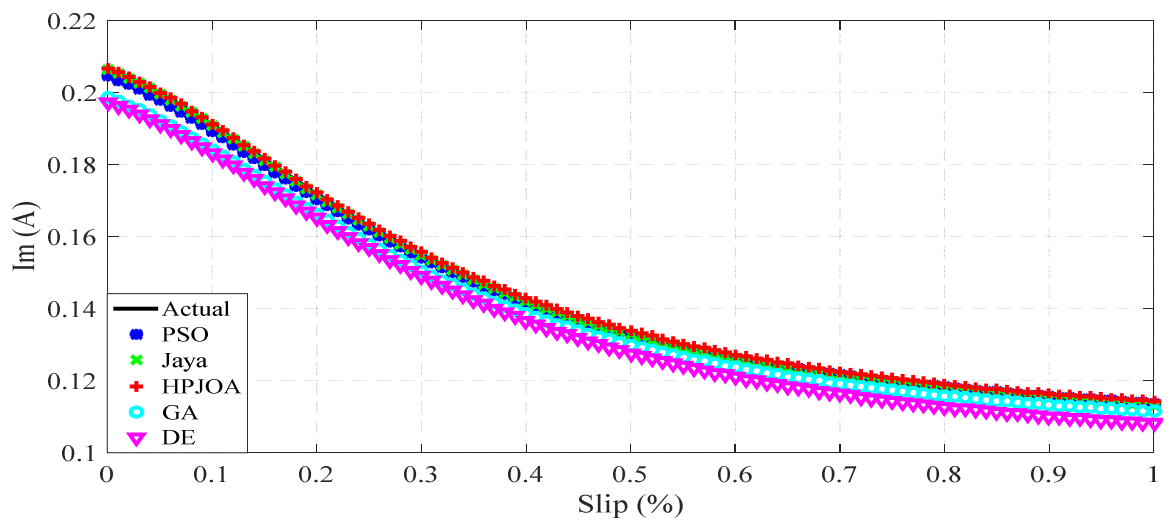
a Stator current - slip



**b** Rotor current - slip

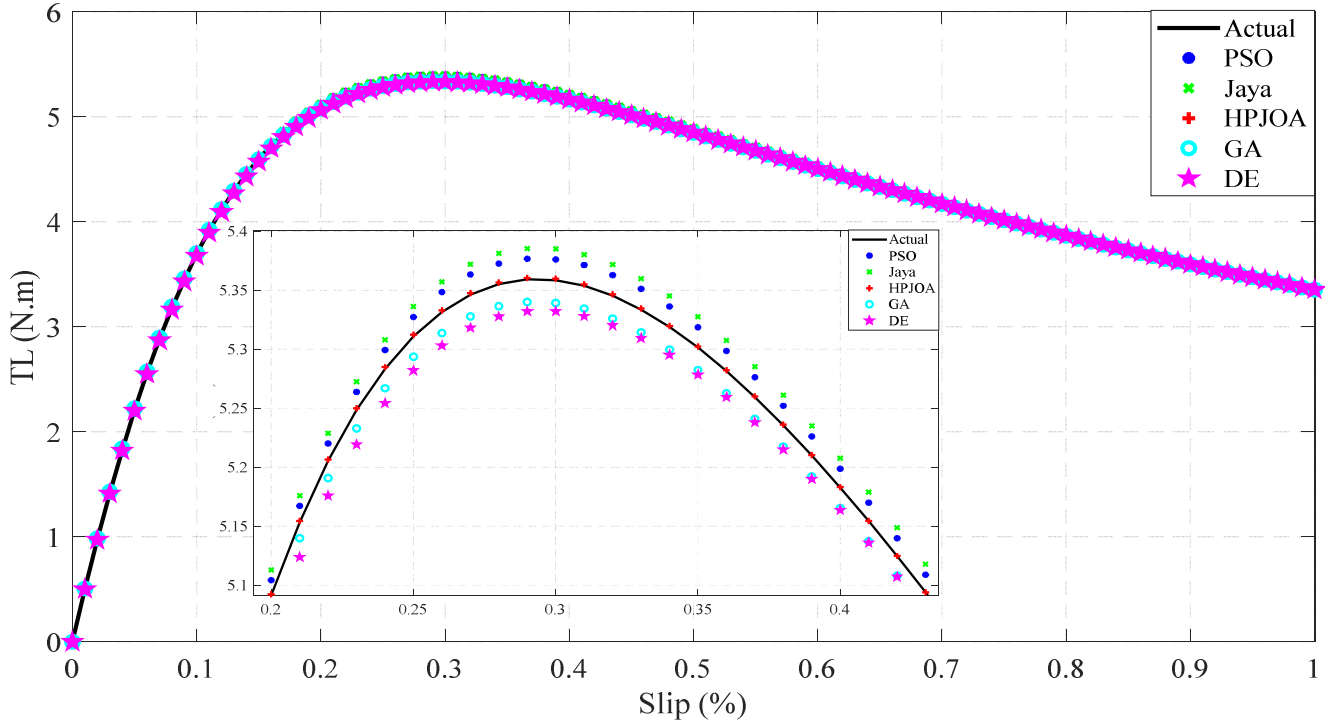


**c** Power factor - slip



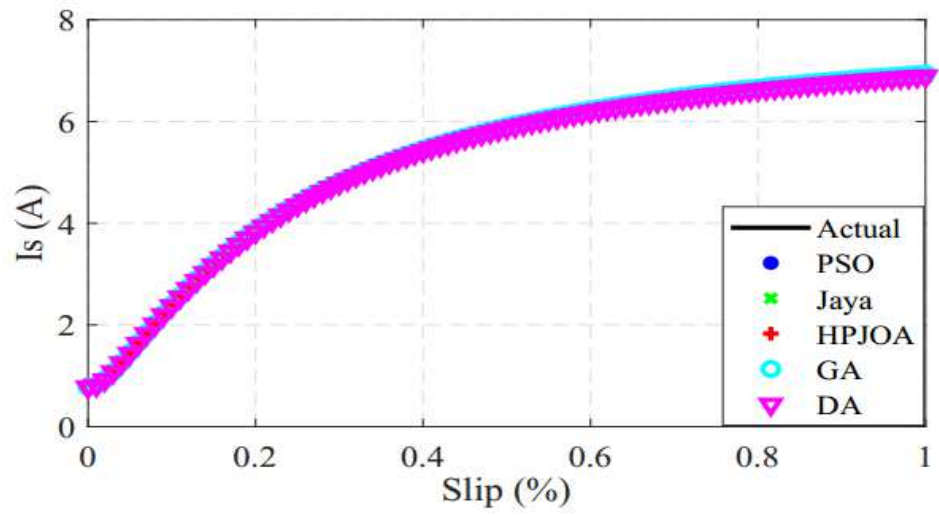
**d** Magnetizing current - slip

**Fig. 6: Performance characteristics of three phase IM**  
(-measurement, \* PSO, × Jaya, o GA, Δ DE, +HPJOA).

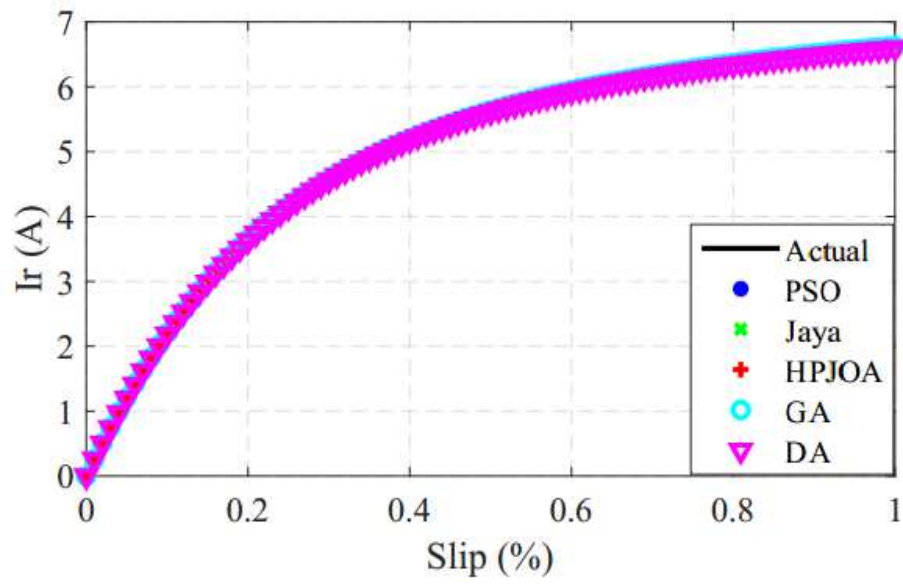


**Fig. 7: Torque - slip characteristics of six phase** (-measurement, \* PSO, × Jaya, o GA, Δ DE, +HPJOA).

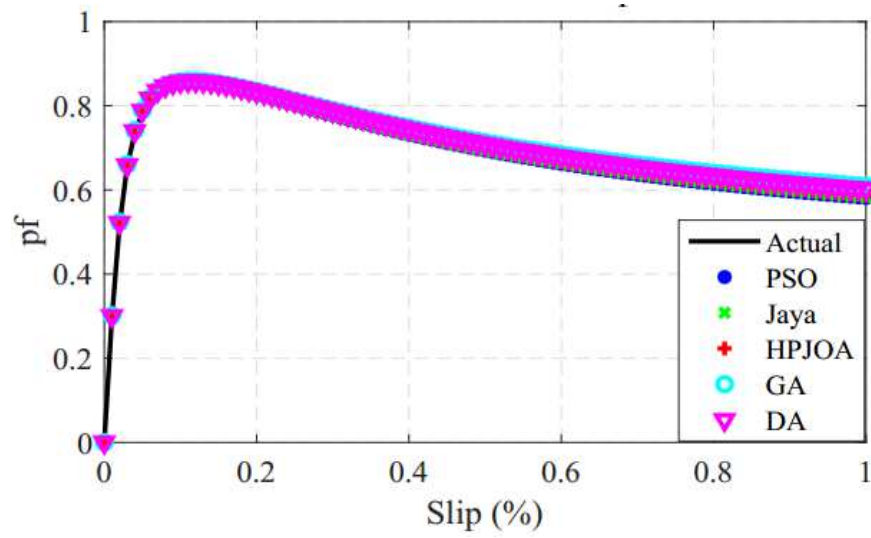
The stator and rotor current -slip characteristics of six-phase induction motor that are based on the parameters calculated by the PSO, Jaya and Hybrid PSO-Jaya are shown in Figures 8a and 8b. Estimated stator and rotor current characteristics using parameters, which are calculated by PSO and Jaya are compared to the measured characteristics, while estimated characteristics using parameters calculated by the Hybrid PSO-Jaya is very close to the real characteristics. The magnetizing current and power factor-slip characteristics of six-phase induction motor using parameters calculated by the PSO, Jaya and HPJOA algorithm are shown in Figure 8 c, d. Estimated magnetizing current and power factor characteristics using parameters calculated by PSO and Jaya has difference compared to the measured characteristics, while estimated characteristics using parameters calculated by the HPJOA is very close to the real characteristics.

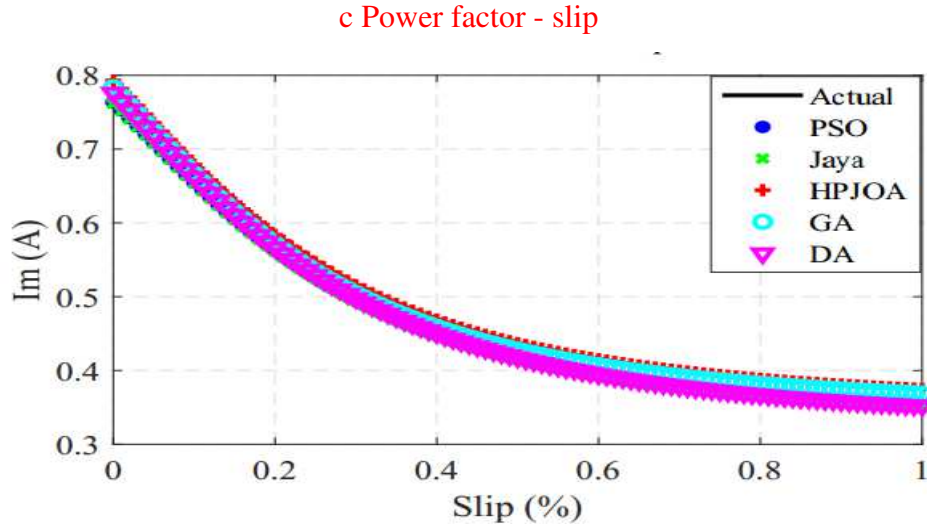


**a** Stator current - slip



**b** Rotor current - slip





d Magnetizing current - slip

**Fig. 8:** Performance characteristics of six phase IM

(-measurement,\* PSO, × Jaya, o GA, Δ DE, +HPJOA).

## 6.1 Competitive tools assessment

### 6.1.1 statistical analysis

Tables 4 and 5 present the statistical indices, mean, median, best, worst, standard deviation and variance, of the competitive algorithms that are carried for 100 iterations and 60 populations, respectively. It is concluded that the proposed HPJOA leads to the best values of the indices compared with PSO, GA, DE and JOA.

### 6.1.2 Convergence rates

The convergence rate of the fitness function of the competitive optimization algorithms are shown in Figure 9 a and b, respectively. It can be seen that from this figure that the proposed HPJOA has better converges rates as the early reaching to final solution provides a proof for fast response compared with other optimization algorithms

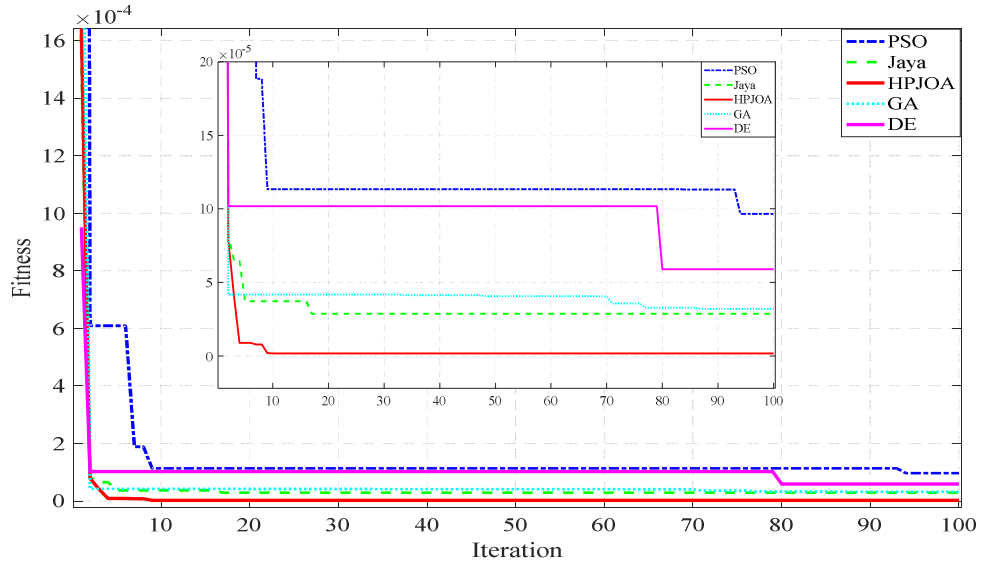
Table 4: Statistical analysis of the competitive methods for the three-phase IM

index	Competitive algorithms				
	GA	DE	PSO	Jaya	HPJOA
Mean	$3.77 \times 10^{-5}$	$6.33 \times 10^{-5}$	$3.2 \times 10^{-5}$	$4.23 \times 10^{-5}$	$3.09 \times 10^{-6}$
Median	$3.43 \times 10^{-5}$	$4.92 \times 10^{-5}$	$2.82 \times 10^{-5}$	$3.74 \times 10^{-5}$	$2.20 \times 10^{-6}$
Best	$4.34 \times 10^{-6}$	$6.86 \times 10^{-6}$	$1.47 \times 10^{-6}$	$2.07 \times 10^{-6}$	$3.59 \times 10^{-7}$
Standard deviation	$2.27 \times 10^{-5}$	$4.49 \times 10^{-5}$	$2.28 \times 10^{-5}$	$2.85 \times 10^{-5}$	$2.43 \times 10^{-6}$
Variance	$5.13 \times 10^{-10}$	$2.01 \times 10^{-9}$	$5.19 \times 10^{-10}$	$8.15 \times 10^{-10}$	$5.91 \times 10^{-12}$

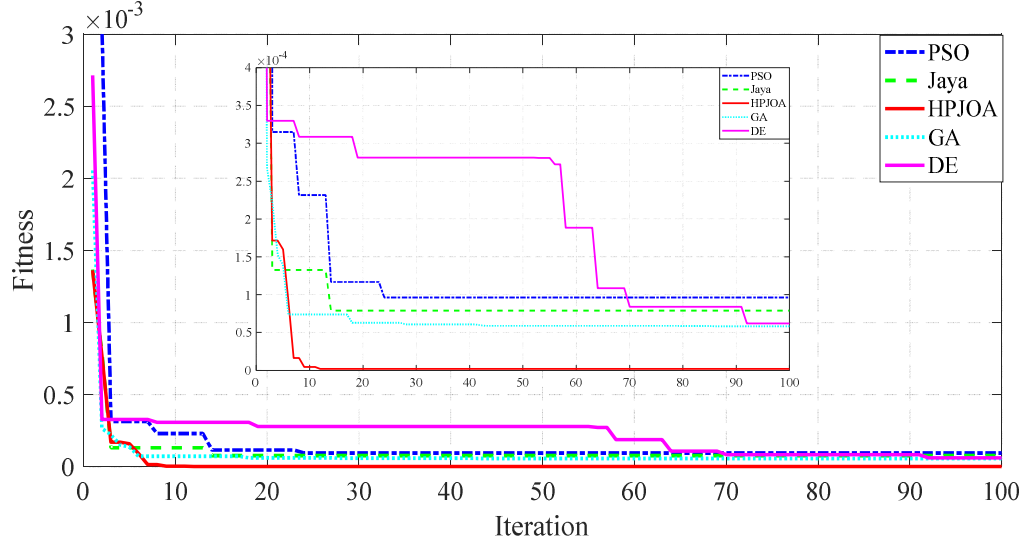
worst	$1.26 \times 10^{-4}$	$2.43 \times 10^{-4}$	$1.22 \times 10^{-4}$	$1.73 \times 10^{-4}$	$1.16 \times 10^{-5}$
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Table 5: Statistical analysis of the competitive methods for the six-phase IM

index	Competitive algorithms				
	GA	DE	PSO	Jaya	HPJOA
Mean	$3.44 \times 10^{-5}$	$7.57 \times 10^{-6}$	$1.87 \times 10^{-5}$	$1.52 \times 10^{-4}$	$5.21 \times 10^{-6}$
Median	$3.04 \times 10^{-5}$	$6.49 \times 10^{-9}$	$8.93 \times 10^{-6}$	$1.22 \times 10^{-4}$	$2.57 \times 10^{-6}$
Best	$5.82 \times 10^{-6}$	$4.07 \times 10^{-7}$	$4.89 \times 10^{-7}$	$9.74 \times 10^{-6}$	$2.30 \times 10^{-7}$
Standard deviation	$1.96 \times 10^{-5}$	$5.78 \times 10^{-6}$	$3.73 \times 10^{-5}$	$1.19 \times 10^{-4}$	$8.18 \times 10^{-6}$
Variance	$3.84 \times 10^{-10}$	$3.34 \times 10^{-11}$	$1.39 \times 10^{-9}$	$1.42 \times 10^{-8}$	$6.69 \times 10^{-11}$
worst	$9.47 \times 10^{-5}$	$2.79 \times 10^{-5}$	$2.89 \times 10^{-4}$	$5.77 \times 10^{-4}$	$4.88 \times 10^{-5}$



(a) 3 phase motor

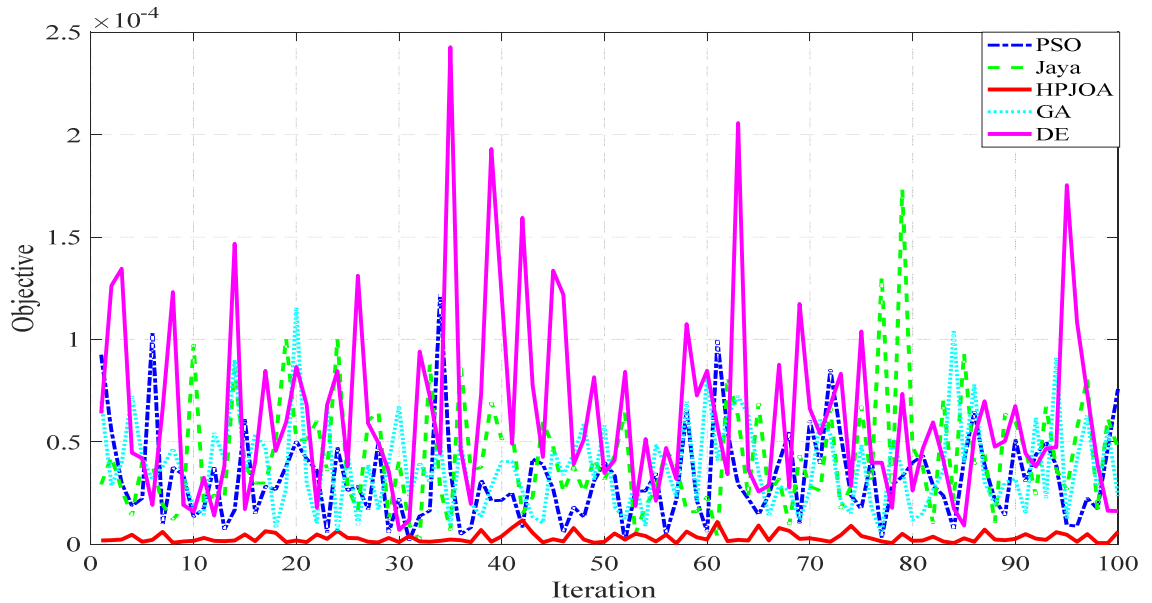


(b) 6-phase motor

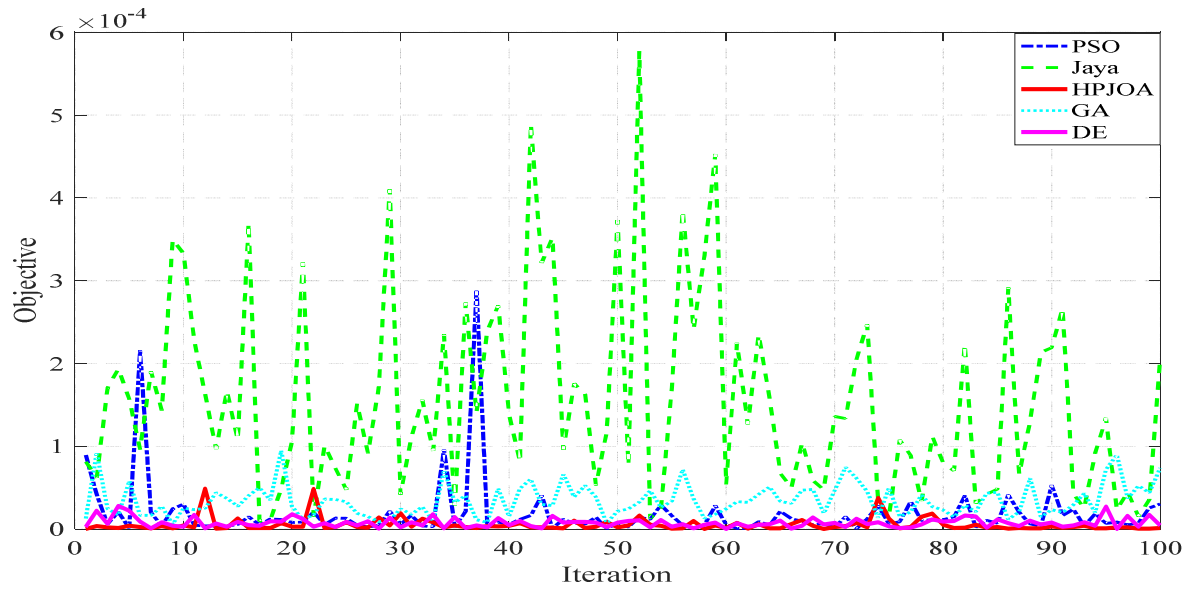
**Fig. 9:** Convergence rates of competitive algorithms (PSO, Jaya, GA, DE and HPJOA)

### 6.1.3 Robustness

To verify the robustness of the competitive algorithms, 100 separate runs are applied on the tested motors. Figure 10 a and b illustrate the robustness of the five algorithms. It is clear that, the proposed HPJOA has the highest robustness compared with PSO, GA, DE and Jaya algorithms. To confirm the fair comparison between the competitive algorithms, we consider the effects of population and maximum iteration variation. Figures 11 and 12 clear that, the proposed HPJOA has the highest robustness, compared with PSO, GA, DE and Jaya algorithm.

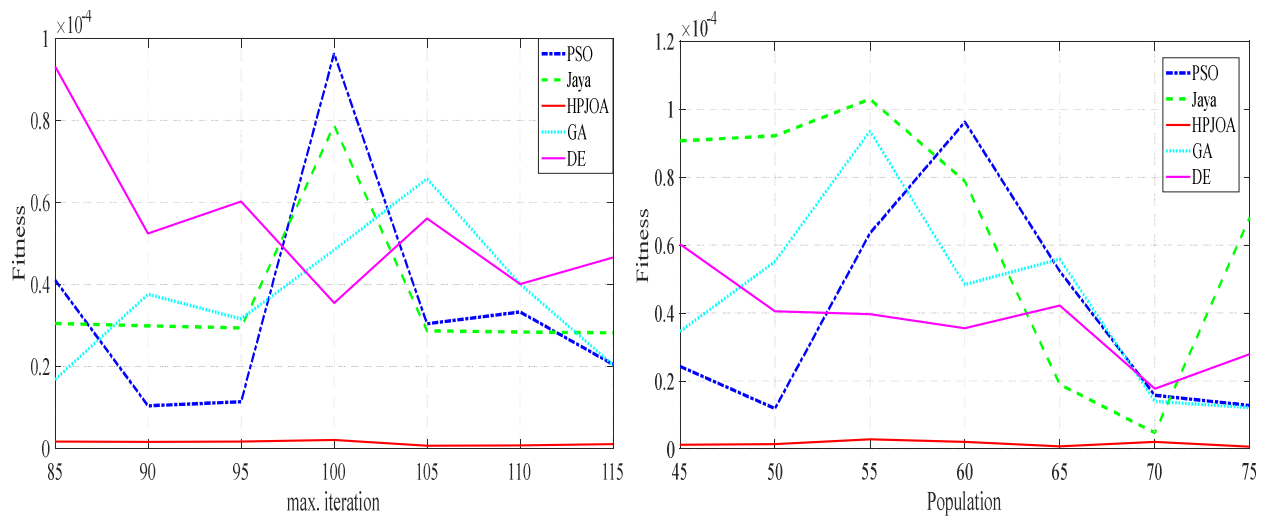


a) 3 phase motor



**b6 phase motor**

**Fig. 10:** Robustness of competitive algorithms (PSO, Jaya, DE, GA and HPJOA).

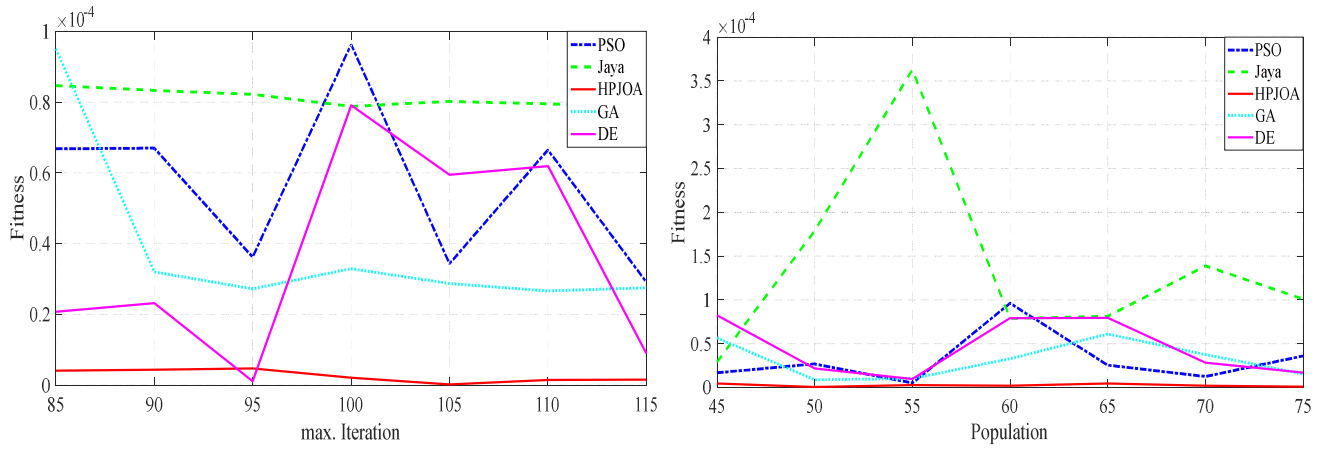


a. variable population at max. iteration =100

b. variable max. iteration at population =60

**Fig. 11:** Fitting of competitive algorithms of three phase induction motor





a. variable population at max. iteration =100b. variable max. iteration at population =60

**Fig. 12:** Fitting of competitive algorithms of six phase induction motor

## 7 Conclusions

This study has presented the parameters estimations of poly-phase induction motors. The HPJOA, Jaya, and PSO algorithm have been used to estimate the parameters of the electrical model of the poly-phase induction motors. The benefits of the proposed HPJOA algorithm have been compared with PSO, JOA, GA and DE for two poly-phase induction motors. The parameters estimation of the competitive algorithms is assessed together the performance of the poly-phase induction motors. Also, the estimated parameters have been compared with the experimental tests. The results indicate the validation and reliability of the suggested hybrid optimization algorithm for efficient extraction of the optimal parameters of three- and six poly phase induction machines. Statistical analyses are provided to assess the competitive algorithms. The robustness of the proposed HPJOA is proved against other competitive algorithms and for varied iteration numbers and population sizes. In addition, the proposed HPJOA realizes fast, stable, and smooth operation characteristic at acceptable convergence rates compared with PSO and Jaya. **The proposed HPJOA achieves the highest reduction of 91.38% and 97.84% that are occurred with the largest fitness function obtained with the competitive algorithms, DE and PSO, for three and six phase motors, respectively.** The statistical indices involve best agreements between the estimated and experimental values for the three optimization algorithms. **It can be concluded that the HPJOA is most simple, stable, and global out performance optimization algorithm.** The use of HPJOA leads to decrease the deviation of estimated parameters compared to PSO and Jaya. Also, the use of HPJOA also enhances the operating performances of the tested PIMs.

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